On Determinants and Consequences of Economic Inequality

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Thesis Defense

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Chapter 1

Labor Market Dynamics after Cost-of-Living Shocks

Motivation

- Renewed interest in the distributional impact of relative price changes
  - For instance, because of income-gradient in energy and food expenditure shares
  - More broadly: price change for goods with low demand elasticities (CoL shocks)
- This project: study relevance of endogenous labor market adjustments as mitigator
  - Do adjustments in nominal earnings compensate for cost increases?
  - What are the channels? (job mobility, bargaining, labor demand, ...)

Data Sources and Approach

- Two Main Data Sources from Germany:
  1. Linked Employer-Employee Panel Data based on Social Security Registry (IAB) + Panel of universe of German establishments
  2. Consumer Expenditure Survey (EVS) from the Federal Statistical Office
- Focus on the case of energy prices and exploit spatial consumption heterogeneity
  1. Estimate energy expenditure shares at the county level in Germany
  2. Use them with energy prices to construct instrument for local cost shocks
  3. Combine with a 20-year panel of employer-employee registry data

Empirical Framework

Consider the outcome of an individual i, living in county c, in year t:

$$y_{ict} = \alpha_i + \gamma_c + \delta_t + \tau \times C^s_{ct} + \mathbf{X_{ict}}\beta + \varepsilon_{ict},$$

where C^s_{ct} measures an individual's cumulative cost increase due to energy price shocks over period s.

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where C^s_{ct} measures an individual's cumulative cost increase due to energy price shocks over period s.

Measure C^s_{ct} as the county-specific energy Consumer Price Index (Laspeyres Approach):

$$C^s_{ct} = \sum_g S^g_{c,t-s} \frac{P^g_t}{P^g_{t-s}},$$

where P^g_t is the price of energy type g and $S^g_{c,t-s}$ is the expenditure share of g.

Identification $S_{c,t-1}$ Prices

Main Empirical Findings

The empirical results indicate that:

1. Individuals are able to recover 36% of county-specific cost increases in the same year

   Main Table IV+Validity Labor Demand

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   Passthrough Over Time

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   Passthrough Over Time

3. Energy price shocks encourage job switches + make them selected for earnings gains

   3.1 Individuals switch to better-paying firms

   3.2 Increased likelihood of switching occupations/sectors

   3.3 $\approx$ 40% of total effect comes from job mobility

   E-E Transitions Characterizing Job Switchers Relative Importance Additional Results

Why Should Employers Compensate Workers for Cost Shocks?

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  - Disutility of labor supply (work longer hours)
  - Cost of Search Effort
  - Utility of non-pecuniary job aspects (e.g., amenities)

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  - Delivers an upward-sloping labor supply curve faced by firms: $L(w)$
  - Combined with non-homothetic preferences for energy: $L(w - q\bar{e})$
  - Generates positive wage adjustments to energy price shocks as a retainment mechanism
    Details

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Chapter 2

Grants vs. Loans: the Role of Financial Aid in College Major Choice

(joint with Adriano De Falco)

Motivation

- Choice of college major is an important investment decision
  - Comparable to the decision of whether to attend university at all
  - Return heterogeneity across majors $\geq$ college premium
    (Patnaik, Wiswall and Zafar, 2020; Kirkeboen, Leuven and Mogstad, 2016)
- Two margins why student loan recipients might differ from grant holders:
  1. Concerns about repayment $\implies$ choice of high return field
  2. Uncertainty about graduation $\implies$ choice of "easy" field

Setting: Chilean Higher Education System

- As in most of Europe: students enroll in institution $\times$ major combination
- High tuition fees relative to family income compared to OECD
  - Ratio of average yearly tuition to family income: ≈ 0.5
  - At 10th percentile of tuition distribution: ≈ 0.24
- State-backed financing of tuition (loan or grant)
- Access to financing determined as a combination of (Details):
  (i) Family income (quintile bins)
  (ii) Standardized Test taken after high school (*PSU*, Details)

Data and Empirical Strategy

Merge several data sources on:

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   - Mifuturo: transparency initiative of Chilean Ministry of Education
   - Provides information on ≈ 250 programs, drawn from past cohorts
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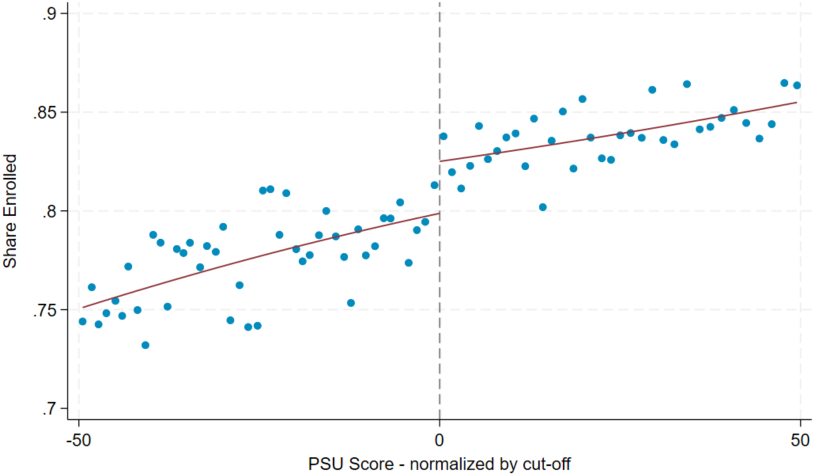
Empirical Strategy: Regression discontinuity design around grant cut-off

Model and Validity Checks

Result I: Grants Increase General Enrollment



Result II: Grants Affect Institution and Program Choices

Students who are marginally eligible for grants are:

- 3 p.p. (11.5%) more likely to enroll in STEM
  - STEM fields are associated with high earnings and dropout rate STEM Chars. More
  - Movements also across other field categories Details
- 3.3 p.p. more likely to enroll in high-quality institutions (CRUCH) Details
- More likely to choose programs with high monetary returns Details

Discrete Choice Model and Estimation

- Consider $j = 1, ..., J$ programs, with $k = 1, 2, ..., K$ characteristics and two groups of students $g = \{Loan, Grant\}$

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$$U_{ij}^{g} = \sum_{k} x_{jk}(\tau_k^g + \beta_k^g PSU_i^*) + \varepsilon_{ij}$$

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$\Longrightarrow$ Our target is $\Delta_k \equiv \tau_k^{Grant} - \tau_k^{Loan}$

Identification

Results of the Discrete Choice Model

- From the model, we estimate that students with access to grants ($\hat{\Delta}_k$, Marginal Effects):
  - Value dropout rates and excess study time significantly *less negatively*
  - Value earnings growth (5 years post-graduation) significantly *more positively*

Results of the Discrete Choice Model

- From the model, we estimate that students with access to grants ($\hat{\Delta}_k$, Marginal Effects):
  - Value dropout rates and excess study time significantly *less negatively*
  - Value earnings growth (5 years post-graduation) significantly *more positively*
- Loans: willing to forgo 6.4% of earnings growth to reduce dropout rates by 1%
- Grants: willing to forgo 3.6% of earnings growth to reduce dropout rates by 1%

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Chapter 3

Are Risk Preferences Shaped by Status Concerns?

(joint with Dietmar Fehr)

Motivation

- Starting point: people care about their relative standing/status

  (Veblen, 1899)

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- Our focus: do such relative concerns alter choices under uncertainty?

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Contribution

1. Provide experimental evidence on link between risk-taking and relative wealth position

Motivation

- Starting point: people care about their relative standing/status

  (Veblen, 1899)

- Our focus: do such relative concerns alter choices under uncertainty?

  (Friedman and Savage, 1948)

Contribution

1. Provide experimental evidence on link between risk-taking and relative wealth position
2. Introduce locus of control as key moderator into analysis

   What is LOC? Why LOC?

Setting and Design

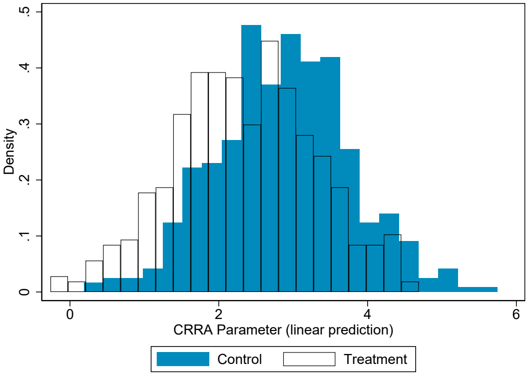
- Data: G-SOEP Innovation Sample ($N \approx 1,000$; companion study of G-SOEP)
- We embed a module into the survey that consists of three parts:

Timing of our Items

1. Personality Questionnaire Details
2. Treatment / Manipulation of Perceptions Details
3. Risk Elicitation / Lottery Choice Details

Main Result: more risk-taking, particularly for external LOC

- Treatment effect corresponds to:
  (i) 0.5 lower CRRA parameter
  (ii) 22% lower probability of choosing risk-free lottery
- 1 S.D. higher LOC amplifies effect by 0.9
- Below median LOC do not react at all



Main Table · Effect on Perceptions · Theory · Lottery Choice Dist.

Thank You!

Appendix to Chapter 1

Identification of τ: Akin to Shift-Share Instrumental Approach

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For τ to be identified in the data, it needs to be the case that:

$$C_{ct}^{s} = \sum_{g} S_{c,t-s}^{g} \frac{P_{t}^{g}}{P_{t-s}^{g}} \perp\!\!\!\perp \varepsilon_{ict} | (\alpha_i, \gamma_c, \delta_t, \mathbf{X_{ict}})$$

- Borusyak, Hull and Jaravel (2022): Identification through exogeneity of shocks
- Goldsmith-Pinkham, Sorkin and Swift (2020): ... through exogeneity of shares
- Obvious confounder: local industry composition and local labor market structure

  $\Longrightarrow$ Adjust for county characteristics and their interaction with yearly fixed effects

Estimating Household Expenditures

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- Since energy is a necessity, $S^{g}_{c,t-s}$ is negatively correlated with local earnings
  - Issue if $\exists$ a shock $Z_t \not\perp \frac{P^g_t}{P^g_{t-s}}$ that differentially affects rich vs. poor

- Approach: use geographic variation adjusted for socio-demographic differences

- Consider expenditure share of energy type g for household h in county c:

$$S^{g}_{hc} = \pi_c + X'_{hc}\beta + u_{hc}$$

where π_c is a location fixed effect, X'_h contains a set of household characteristics, and $g \in \{Gas, Gasoline, Electricity, Oil, Other\}$.

$\Longrightarrow$ use EVS data to estimate π_c and predict S^g_c, keeping X'_{hc} at sample mean

Distribution | Time Stability | Spatial Distribution | By Sub-component | Energy Mix | Correlates

Energy Expenditure Shares across counties

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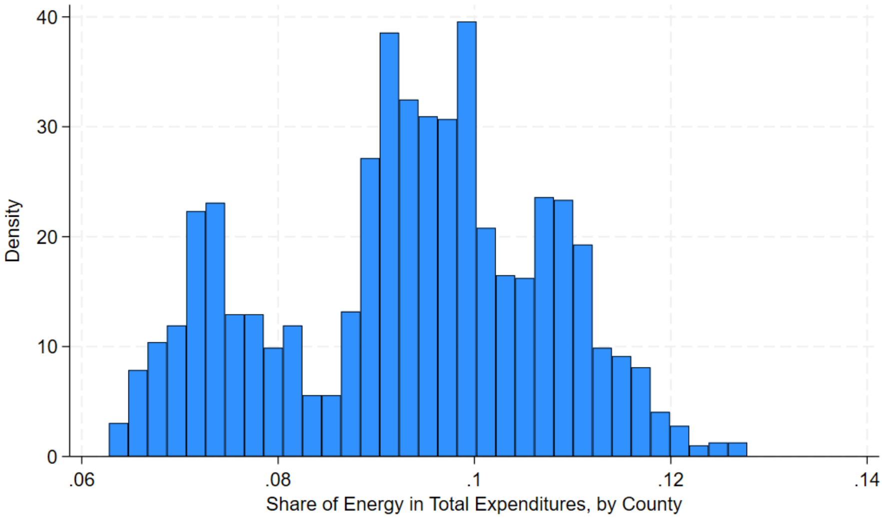

Characterizing High and Low Energy Expenditure Counties

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Table: Correlation Coefficients of Expenditure Shares with County Characteristics

	Population	Population Density	Commuter Share
Energy Exp. Share	-0.217	-0.499	0.090
	(0.000)	(0.000)	(0.011)
	New Housing	Access to Public Transport	Dist. to Regional Center
Energy Exp. Share	-0.189	-0.469	0.689
	(0.000)	(0.000)	(0.000)

Notes: Commuter share is the share of all employees that commute $>$ 50km. Access to Public Transport is the share of inhabitants that live within a 1km radius of a stop for public transport offering at least 20 rides a day. New Housing is the fraction of newly built housing units per 1,000 existing housing units. Distance to Regional Center measures the time in minutes it would require an average inhabitant to reach a regional center (*Oberzentrum*) by car. P-values in parentheses.

Consumer Prices for Energy Types over Sample Period

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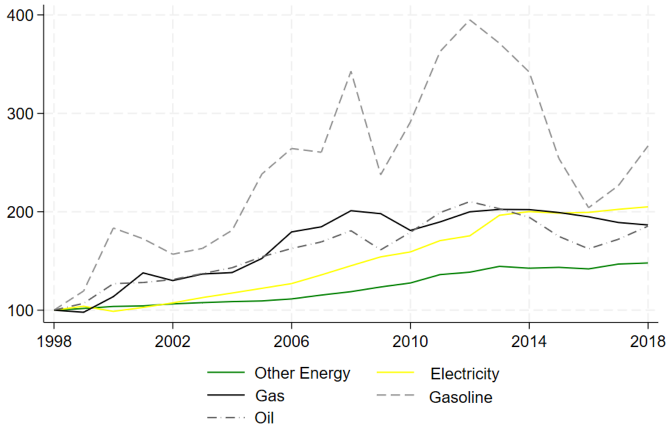

Average Effect on Earnings

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Table: The Effect of Year-to-Year Energy Cost Shocks on Earnings

	$Outcome = ln(earnings_{it}/earnings_{i,t-1})$				
	(1)	(2)	(3)	(4)	(5)
Yearly Cost Shock	0.427^{***}	0.436^{***}	0.361^{***}	0.385^{***}	0.360^{***}
	(0.057)	(0.049)	(0.049)	(0.070)	(0.045)
N Individuals	869,437	869,395	869,379	869,437	868,794
N Total	9,890,000	9,887,582	9,887,145	9,890,000	8,858,287
Match HHI		✓			✓
Match Energy-Intensity			✓		✓
Match Unemployment				✓	✓

Notes: $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors are clustered at the county level. Yearly Cost Shock is measured as: $C^1_{ct} = \sum_g S^g_{c,t-1} \frac{P^g_t}{P^g_{t-1}}$.

Average Effect on Earnings

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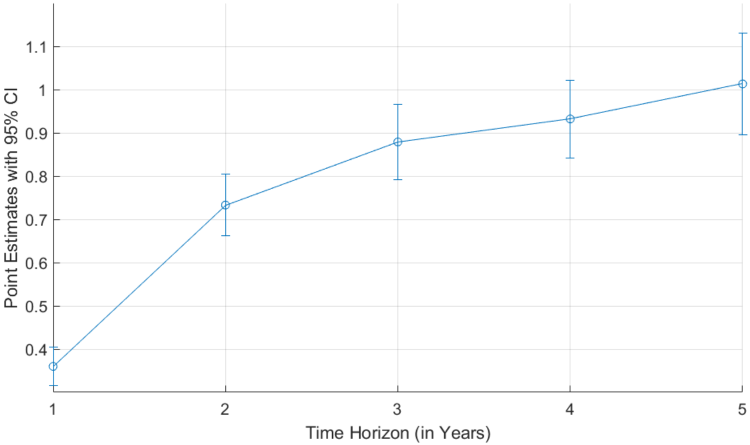
Figure: The Effect of Energy Cost Shocks on Income; for varying time-horizons



The Job-to-Job Mobility Margin

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Table: The Effect of Energy Cost Shocks on Job-to-Job Mobility

	Pr(E-to-E)	$\Delta ln(earnings)$	
	(1)	(2)	(3)
Yearly Cost Shock	0.297***	0.268***	0.840***
	(0.120)	(0.035)	(0.218)
Sample	Full	Stayers	Switchers
N Individuals	869,752	386,020	805,334
N Total	9,923,313	1,373,675	8,257,784

- Higher energy costs (i) encourage job mobility and (ii) make transitions more targeted

Additional Results

Additional results include that in response to higher energy costs:

1. Workers are less likely to commute out of county for work ▷
2. Workers do not switch from part- to fulltime ▷
3. Aggregate employment responds (weakly) positively ▷
4. Pass-through and job mobility vary considerably across subgroups ▷

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Other Margins of Adjustment: Hours Worked

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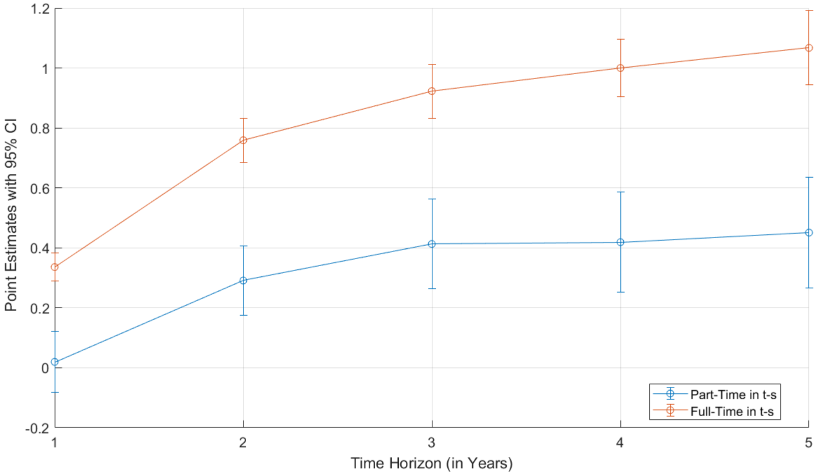
- No Data on Hours worked, but: limited response of part-time workers



Other Results: Treatment Heterogeneity

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- There is considerable pass-through heterogeneity:
  - Younger workers are more mobile and experience stronger earnings responses ▷
  - The same is true for uni graduates ▷
  - Little Difference between genders, but larger job mobility of women ▷
- E-E transitions are more targeted in high-exposure counties, but within a county, the return is heterogeneous across subgroups

Model Environment

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- Set of local labor markets $l \in \{1, 2, ..., L\}$, inhabited by a finite set of firms $j \in J_l$
  - Firms are distributed across sectors $s \in S$
  - They produce using sectors-specific technology with labor and energy as inputs
- Mass of workers N_l choose:
  1. Which firm j to work for
  2. Consumption of c (produced by firms, sold competitively at p)
  3. Consumption of e (supplied exogenously at price q)
- No savings: firms and workers optimize myopically and locally
  1. Realization of productivity and energy price
  2. Firms post wages
  3. Workers observe wage offer distribution and sort
  4. Production and consumption takes place

Worker's Problem I: Consumption, conditional on working for j

Consumption problem when employed at firm j at wage w_{jt}, is:

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$$\max_{c_t, e_t} \{\gamma ln(c_t) + (1-\gamma) ln(e_t - \bar{e}_l)\} \quad s.t. \quad p_t c_t + q_t e_t = w_{jt}$$

which delivers:

1. The indirect utility function: $V(w_{jt}, p_t, q_t, \bar{e}) = ln(w_{jt} - q_t \bar{e}) + \Lambda(p_t, q_t) \equiv V_{jt}$
2. The energy expenditure share: $\frac{q_t e_t^*}{w_{jt}} = (1-\gamma) + \gamma \frac{q_t \bar{e}}{w_{jt}}$

Worker's Problem II: Choosing Firm j

Combine this consumption problem with modern monopsony models of differentiated firms (Card et al., 2018; Lamadon, Mogstad and Setzler, 2022; Berger, Herkenhoff and Mongey, 2022):

$$j(it) = \max_j \{V_{jt} + \xi_{ijt}\}$$

- ξ_{ij}: worker-specific evaluation of amenities of firm j
  - Can allow for horizontal and vertical differentiation: $\xi_{ijt} = \bar{\xi}_j + \tilde{\xi}_{ijt}$

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- For now, let $F(\{\xi_{ijt}\}) = exp\left[-\sum_s \left(\sum_{j \in J_s} e^{-\xi_{ijt}\eta}\right)^{\frac{\theta}{\eta}}\right]$ and $\forall j : \bar{\xi}_j = 0$
- Each period, a fraction π draws a new taste-shock

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- Each period, a fraction π draws a new taste-shock

The assumed taste-shock distribution and the value function from the previous slide imply:

$$Pr(j|s) = \frac{exp(\eta V_{jt})}{\sum_{j'\in J} exp(\eta V_{j't})} = \frac{(w_{jt} - q_t\bar{e})^{\eta}}{M_{st}}, \quad Pr(s) = \frac{M_{st}^{\frac{\theta}{\eta}}}{\sum_{s'\in S} M_{s't}^{\frac{\theta}{\eta}}}$$

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Firm's Problem

Firms produce c using labor and energy as inputs:

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$$\max_{w_{jt}, E_{jt}} = p_t z_{jt} f_{s(j)}(L_{jt}, E_{jt}) - w_{jt} L_{jt} - q_t E_{jt}$$

$$\text{s.t.} \quad L_{jt} = N \times Pr(j|s) \times Pr(s)$$

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Standard monopsony case: $w_{jt} = \underbrace{\frac{\varepsilon_{jt}}{1+\varepsilon_{jt}}}_{Mark-Down} \times \underbrace{p_t z_{jt} \frac{\partial f_{s(j)}(L_{jt}, E_{jt})}{\partial L_{jt}}}_{MRPL},$

- where ε_{jt} is the elasticity of labor supply to firm j at current prices

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- where ε_{jt} is the elasticity of labor supply to firm j at current prices
- Following Lamadon, Mogstad and Setzler (2022), model firms as atomistic, then:

$$\varepsilon_{jt} = \frac{w_{jt}}{Pr(j)} \frac{\partial Pr(j)}{\partial w_{jt}} = \frac{w_{jt}\eta}{w_{jt} - q_t \bar{e}} \implies w_{jt} = \frac{\eta}{1+\eta} MRPL + \frac{1}{1+\eta} q_t \bar{e}$$

Discussion of Baseline Model

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- ▷ Main Mechanism: Shock to costs-of-living increases marginal utility of income
  - Increase in labor supply elasticity changes firm-worker rent-sharing in favor of workers
  - But: some workers pay by giving up on amenities

  $\Longrightarrow$ Welfare costs not fully described by changes in real consumption
  (see also Afrouzi et al., 2024; Guerreiro et al., 2024)

- ▷ Even with little "mobility" in equilibrium: model predicts pos. wage adjustments

- ▷ The mechanism's relevance hinges on the elasticity of demand

  $\Longrightarrow$ Results have higher external validity for shocks to housing, food, ...

Estimation (Next Steps)

Next step: Take the prediction of a drop in amenity values seriously (try to quantify it). To do so:

1. Set $f_{s(j)}(L_{jt}, E_{jt}) = \left[L_{jt}^{1-\gamma_{s(j)}} E_{jt}^{\gamma_{s(j)}}\right]^{\alpha}$ and calibrate parameters externally (von Graevenitz and Rottner, 2023; Lamadon, Mogstad and Setzler, 2022)

2. Estimate $\Theta = \{\eta, \theta, \pi, \mu, \bar{\mathbf{e}}_{\mathbf{l}})$ and productivity processes by matching:
    - E-E transition rates and elasticities to energy prices (within and across sectors)
    - Wage elasticity to energy prices (average + conditional on switching)
    - Cross-sectional distribution of earnings and earnings transitions
    - County-level energy expenditure shares

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Stability of County Predictions over Time

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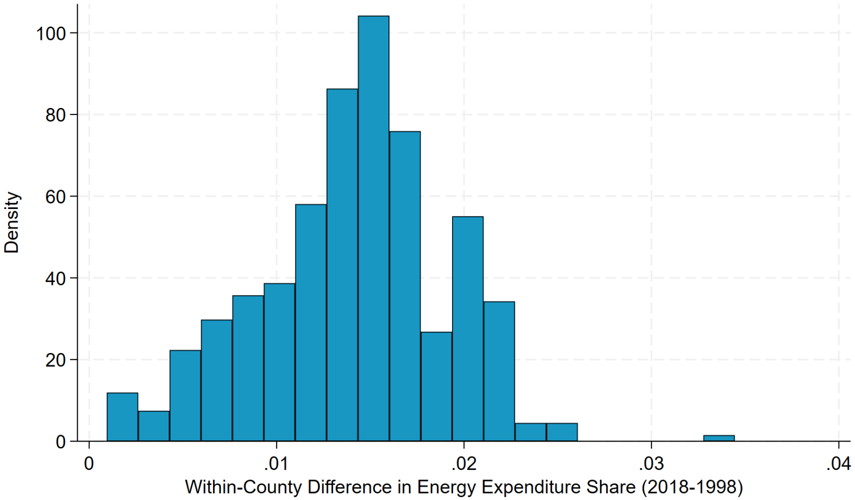

Distribution of Energy Shares Across Counties, 2018

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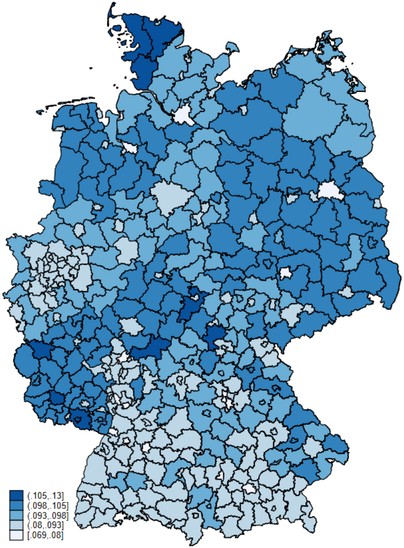

Energy Mix is Stable Across Expenditure Levels

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Table: Share of Energy Types in Total Energy Expenditures (in %)

Energy Expenditure Quartile	Q1	Q2	Q3	Q4
Gasoline	42.0	41.5	41.2	41.6
Gas	11.2	13.6	16.0	14.7
Oil	6.2	7.2	7.0	9.7
Electricity	26.2	26.7	26.2	25.2
Other Energy	14.4	11.1	9.6	8.8

Notes: The table shows estimated county-level averages for expenditure shares of different types of energy goods relative to total energy expenditures. Based on EVS waves 1993, 1998, 2003, 2008, 2013, and 2018. *Other Energy* includes expenditures for coal, wood, other solid fuels, and central heating.

Summary Statistics for Expenditure Shares

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Table: Expenditure Shares for Different Energy Types (in %)

	Mean	*S.D.*	*Min*	*Max*
Gasoline	3.75	0.67	1.79	6.63
Gas	1.25	0.51	0.25	2.76
Oil	0.71	0.37	0.01	2.14
Electricity	2.46	0.35	1.6	3.36
Other Energy	1.13	0.47	0.23	3.27
All Energy	9.31	1.2	6.83	12.74

Notes: The table shows estimated county-level averages for expenditure shares of different types of energy goods, based on EVS waves 1993, 1998, 2003, 2008, 2013, and 2018. *Other Energy* includes expenditures for coal, wood, other solid fuels, and central heating.

Effect of Cost Shocks on Earnings, Robustness

Back

Table: The Effect of Year-to-Year Energy Cost Shocks on Earnings

	$Outcome = ln(earnings_{it}/earnings_{i,t-1})$			
	(1)	(2)	(3)	(4)
Yearly Cost Shock	0.536***	0.428***	0.417***	0.423***
	(0.064)	(0.060)	(0.062)	(0.065)
1st Lead Cost Shock			-0.009	-0.019
			(0.056)	(0.075)
2nd Lead Cost Shock				0.008
				(0.059)
	Carbon IV	Top-Coded Wages		

Notes: $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors are clustered at the county level. Yearly Cost Shock is measured as: $C^1_{ct} = \sum_g S^g_{c,t-1} \frac{P^g_t}{P^g_{t-1}}$.

(Naive) Back-of-the-Envelope Decomposition

Back

- On average, 16% of the sample switches employers in a given year
- For the average switcher (stayer) in the sample, $ln\left(\frac{Earnings_{ict}}{Earnings_{ic,t-1}}\right) = 0.06\ (0.024)$
- Based on this and the estimates on the previous slide:
  1. The increased job mobility explains 3.1% of the average response
  2. More selected transitions explain 37.3% of the average response
  3. The interaction of the two explains $< 1\%$

$\Longrightarrow$ Over half of the response in nominal earnings due to changes for stayers

Labor Demand Responses

Back

- von Graevenitz and Rottner (2023): 2-3% of total costs due to energy
  - Estimates are for the German manufacturing sector between 2003 and 2017
  - Mostly driven by electricity and gas
  - Excluding gas or electricity does not affect results ▷
- Petrick, Rehdanz and Wagner (2011) identify sectors with highest within-sector variance of energy intensity
  - These are the sectors that are most likely to be problematic (allow for variation across space)
  - Excluding counties with high/low share of employment in these sectors does not affect results ▷

Effect of Cost Shocks on Earnings, by Energy Type

Back

Table: The Effect of Year-to-Year Energy Cost Shocks on Earnings

		Exclude:				
		Gasoline	Gas	Oil	Electricity	Other Energy
Yearly Cost Shock		0.505***	0.452***	0.489***	0.484***	0.357***
		(0.074)	(0.069)	(0.069)	(0.060)	(0.059)
Gasoline	0.563***					
	(0.094)					
Gas	0.523***					
	(0.124)					
Oil	0.240***					
	(0.092)					
Electricity	0.133					
	(0.211)					
Other Energy	0.468**					
	(0.191)					

Variance in Energy-Intensity within Sectors

Back

Table: Pass-Through When Dropping Counties with High (Low) Share of Employment in Sectors with High Variance in Energy-Intensity

	$Outcome = ln(earnings_{it}/earnings_{i,t-1})$			
	(1)	(2)	(3)	(4)
Yearly Cost Shock	0.427^{***}	0.404^{***}	0.388^{***}	0.389^{***}
	(0.057)	(0.061)	(0.064)	(0.053)
	Full	Drop Top 10%	Drop Top 20%	Drop Bottom & Top 10%

Notes: $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. Standard errors are clustered at the county level. Yearly Cost Shock is measured as: $C^1_{ct} = \sum_g S^g_{c,t-1} \frac{P^g_t}{P^g_{t-1}}$.

Effect Heterogeneity by Age

Back

Table: Effect of Energy Cost Shock on Earnings and Job Mobility, by Age

Outcome	Early (age 25-40)	Mid (41-55)	Late (56-65)
$\Delta ln(income), yearly$	0.665^{***}	0.190^{***}	-0.030
	(0.119)	(0.041)	(0.126)
$Pr(E-E), yearly$	0.398^{**}	0.177	0.009
	(0.141)	(0.123)	(0.213)
N Individuals	568,595	521,052	205,405

Effect Heterogeneity by Educational Attainment

Back

Table: Effect of Energy Cost Shock on Earnings and Job Mobility, by Education

Outcome	Below Abitur	Abitur	Academic
$\Delta ln(income), yearly$	0.295***	0.291***	0.718***
	(0.044)	(0.109)	(0.103)
$Pr(E-E), yearly$	0.252**	0.022	0.446***
	(0.116)	(0.184)	(0.157)
N Individuals	610,794	124,986	166,422

Why Are Transitions More Effective in High-Exposure Counties?

Back

Table: Energy Cost Shocks and the Characteristics of Switcher's New Firms

	Expected Change in:	Pr(Switch to Different:)		
	$ln(earnings)$	Sector	Occupation	Task
Energy Cost Shock	0.343*	0.573***	0.487***	0.089
	(0.181)	(0.182)	(0.169)	(0.135)

Other Margins of Adjustment: Extensive Margin

Back

- Aggregate employment responds (weakly) positively; little scope for increase in the MPL
  - 1 S.D. shock $\approx$ 0.1 p.p. lower unemployment rate
- Higher employment + higher earnings suggest presence of labor market frictions

Table: Effect on Firm-Level Employment

	$\Delta ln(\#employees)$	UE Rate
	(2)	(3)
Energy Cost Shock	0.216**	-0.080***
	(0.102)	(0.016)
N Firms/Counties	400	400
N Total	8,000	8,000
Data	IAB-BHP	BBSR

Effect Heterogeneity by Citizenship and Gender

Back

Table: Effect of Energy Cost Shock on Earnings and Job Mobility, by Subgroup

	Gender		Nationality	
	Male	Female	Non-German	German
$\Delta ln(income), yearly$	0.381***	0.481***	-0.057	0.447***
	(0.052)	(0.078)	(0.133)	(0.060)
$Pr(E-E), yearly$	0.105	0.540***	0.280	0.275**
	(0.120)	(0.138)	(0.225)	(0.116)

Appendix to Chapter 2

Empirical Model and Estimation

Back

- Our estimand of interest is the standard Sharp RD parameter:

$$\tau_{SRD} = \lim_{z \to 0^+} \mathbb{E}[Y_i | PSU_i^* = z] - \lim_{z \to 0^-} \mathbb{E}[Y_i | PSU_i^* = z]$$

- In practice, we estimate weighted local linear regressions:

$$\begin{aligned} Y_i = \beta_0 &+ \beta_1 \mathbb{1}\{PSU_i^* \geq 0\} \\ &+ \beta_2 \mathbb{1}\{PSU_i^* \geq 0\} \times PSU_i^* + \beta_3 PSU_i^* + X_i' \delta + \varepsilon_i \end{aligned}$$

Grant Take-Up McCrary Test Balance Test

Effect of Being Eligible for Grants (Sharp RDD)

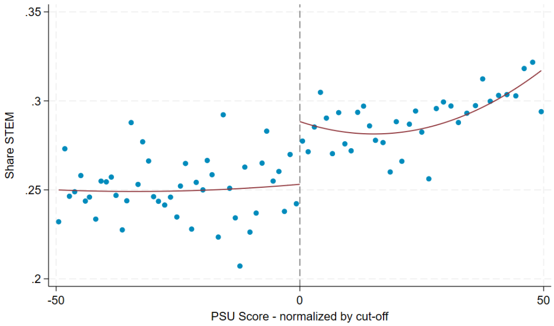
Back

Table: Optimal Bandwidth

	STEM (=1) (1)	Engineering (=1) (2)	Sciences (=1) (3)
RD Estimate	0.029***	0.024***	0.005*
	(0.008)	(0.007)	(0.003)
Baseline Mean	0.253	0.232	0.021
Bandwidth	41	44	46
Effective N	52,004	55,560	62,118

Heterogeneity | Placebo Test | Different bandwidths | Marginal Enrollees vs. Major Switchers

Figure: Non-parametric Evidence



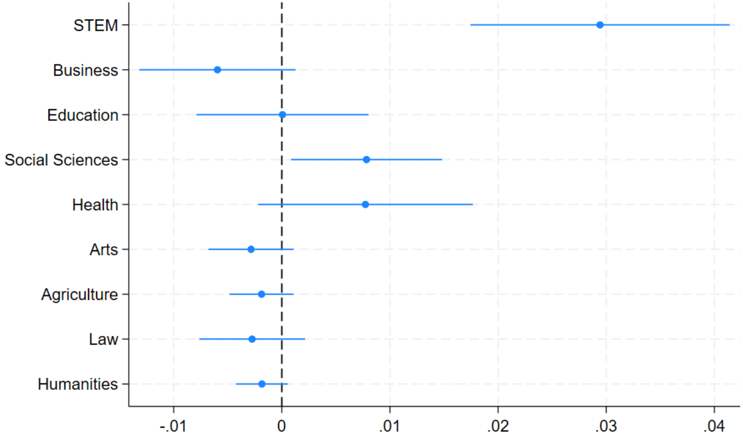
Grants vs. Loans: Characterizing Chosen Programs

Back

	Enrolled in:		
	Low	Medium	High
Earnings, year 5	-0.017*	-0.005	0.022**
	(0.010)	(0.010)	(0.009)
Earnings Growth, year 1 to 5	-0.010	-0.008	0.019*
	(0.010)	(0.012)	(0.011)
Pr(Employed_y1)	-0.032***	0.026***	0.006
	(0.011)	(0.010)	(0.010)
Pr(Dropout_y1)	0.007	0.009	-0.016
	(0.012)	(0.012)	(0.012)
Excess Study Time	-0.019*	0.008	0.011
	(0.011)	(0.011)	(0.009)

Effect of Grant Eligibility on All Fields

Back



RD Estimates on General Enrollment

Back

Table: Effect of Grants vs. Loans on Enrollment in Different Institution Types

	Enrolled in...			
	Any Institution	CRUCH	Private Uni	Vocational
RD_Estimate	0.033***	0.033***	0.008	-0.006
	(0.008)	(0.010)	(0.008)	(0.007)
Baseline Mean	0.797	0.357	0.295	0.146
Bandwidth	32	32	41	34
Effective N	41,675	41,675	52,222	44,191

Prueba de Selección Universitaria (PSU)

Back

- Administered country-wide in early December by *DEMRE* (part of UChile)
- Nationally standardized multiple choice test:
  - Two mandatory components: *Mathematics* and *Language*
  - At least one of: *Science* or *History, Geography, and Social Science*
  - Results are standardized ($\mu = 500$, $\sigma = 110$, Range: 150–850)
- Only average of mandatory fields used for grant eligibility

Eligibility Criteria for Grants

why excluding 500?

Back

Table: PSU Threshold for Grant Eligibility

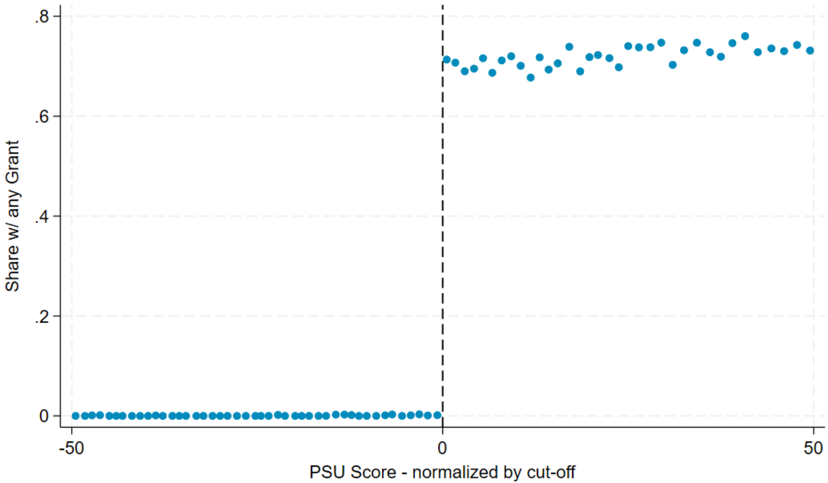
Bicentennial and Juan Gomez Millas (JGM)				
	2012	*2013*	*2014*	*2015*
Quintile 1	550	500	500	500
Quintile 2	550	525	525	500
Quintile 3	550	550	550	500
$>$ *Quintile 3*	N.E.	N.E.	N.E.	N.E. / 500

Note: Displayed are the minimum test score averages of math and language that grant eligibility to either of the two scholarships, by year and family income quintile. N.E.: not eligible. Bicentennial and JGM grants are received conditional on enrolling in CRUCH and accredited universities, respectively.

First Stage: Take-Up of Grants around Cut-off

Back

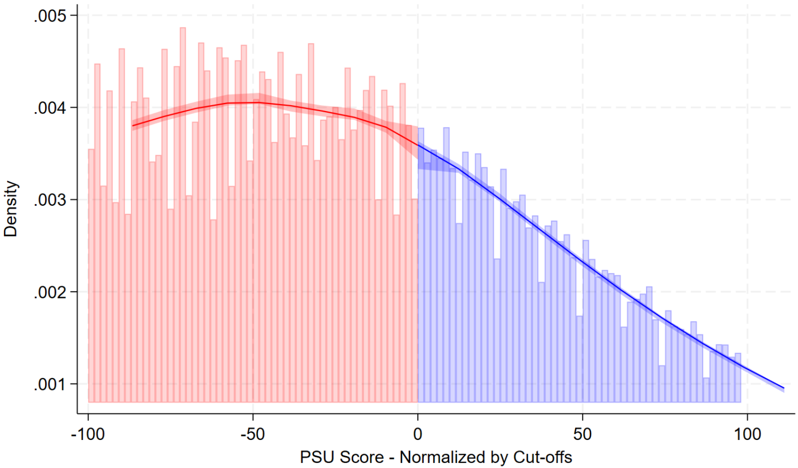
Figure: Take-up of any grant in 1.25 PSU point bins



Identification: No Sorting

Back

Figure: McCrary Test for Discontinuity in Running Variable



Identification: Continuity Potential Outcomes

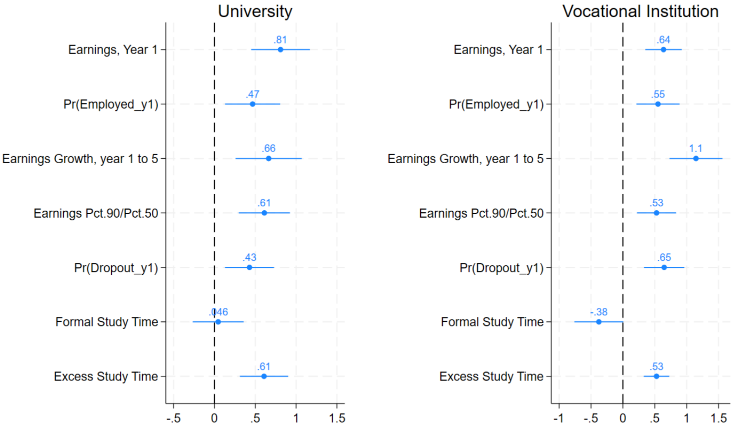
Back

Table: Covariate Balance around Grant Eligibility Cut-off

	Baseline (β_0)	RD Estimate (β_1)	SE ($\hat{\beta}_1$)
High School GPA	5.725	0.002	0.008
# Working Family Members	1.159	-0.001	0.011
# Studying Family Members	0.100	-0.004	0.005
Female	0.540	0.004	0.007
Single Mother HH	0.188	-0.004	0.004
Academic Parents	0.445	-0.015**	0.009
Took Science Test	0.667	0.002	0.009
Municipal School	0.271	-0.007	0.004
Subsidized School	0.673	-0.010**	0.004
Academic School	0.809	-0.006	0.006

STEM vs. No-STEM Differences in Program Characteristics

Back



Note: The Figure uses data from *MiFuturo* at the program-level. Each row displays point estimates and 95% confidence intervals for β_1 from regressions of the type $X_i = \beta_0 + \beta_1 STEM_i + u_i$, where X_i are the respective displayed program characteristics. Program characteristics are standardized to a mean of zero and standard deviation of one. The left column uses only programs offered at universities, whereas the right column uses programs in vocational institutions. Programs are weighted by the number of enrollees.

Discrete Choice Model Estimates (τ_k^g and Δ_k)

Back

	(1) Loans	(2) Grants	(3) $\Delta_k = (2) - (1)$
Excess Study Time	-0.022	0.051	0.073*
	(0.028)	(0.033)	(0.043)
Pr(Dropout_y1)	-0.489***	-0.396***	0.093**
	(0.038)	(0.027)	(0.047)
Earnings, year 1	0.015	-0.026	-0.041
	(0.039)	(0.035)	(0.052)
Earnings Growth, year 1 to 5	0.166***	0.241***	0.075**
	(0.024)	(0.020)	(0.032)
Pr(Employed_y1)	0.137**	0.127**	-0.011
	(0.056)	(0.059)	(0.081)
N Individuals	10,932	10,394	
N Programs	246	246	

Heterogeneity: Effect on STEM by Subgroups

		Gender	
	Male	Female	Δ of Coefficients
RD_Estimate	0.042***	0.020**	-0.022
	(0.013)	(0.008)	(0.015)
Baseline Mean	0.398	0.130	
Effective N	28,167	27,210	
		Parental Education	
	Second-Gen	First-Gen	Δ of Coefficients
RD_Estimate	0.025***	0.033***	0.008
	(0.009)	(0.010)	(0.013)
Baseline Mean	0.251	0.252	
Effective N	28,202	28,344	
		Parental Income	
	Quintile 2+3	First Quintile	Δ of Coefficients
RD_Estimate	0.028***	0.034**	0.006
	(0.008)	(0.017)	(0.019)
Baseline Mean	0.255	0.243	
Effective N	42,475	12,969	

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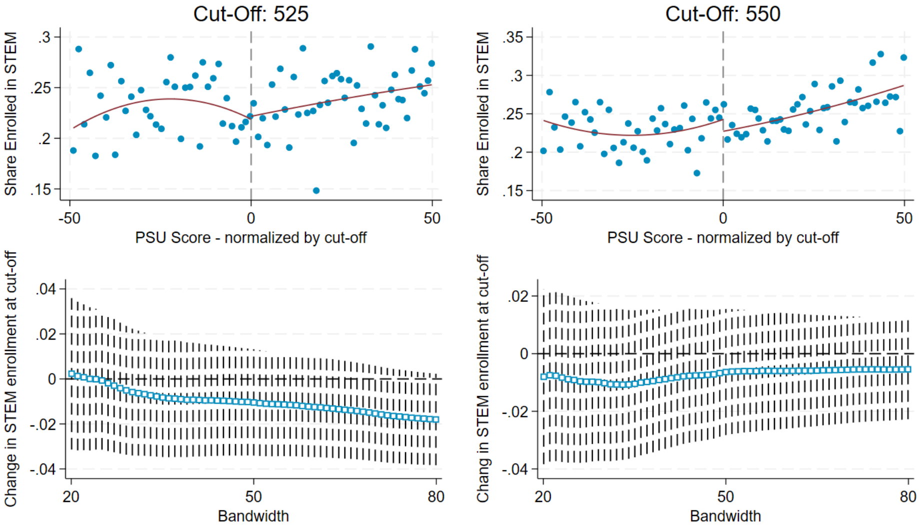
Placebo Test: RD Estimate on Non-Eligible Population

Back



RD Estimates for Various Bandwidths

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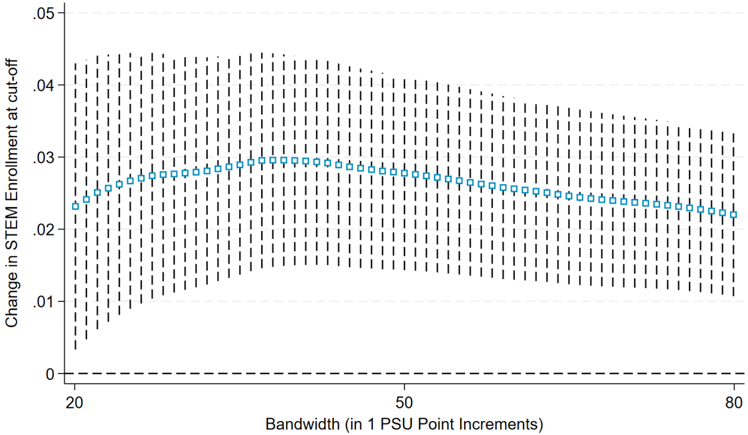
Figure: Effect on STEM Enrollment



Hypothetical Major Distribution

Balance|Enrollment Back

Table: Hypothetical and Observed Change in Enrollment by Field at the Cut-off

	Below the cut-off (in %) (1)	Hypothetical Change (2)	Observed Change (3)
STEM	25.3	1.1	2.9
Business	10.7	0.4	-0.3
Education	10.0	0.4	0.7
Social Science	6.6	0.3	0.6
Health	16.5	0.7	0.6
Arts & Architecture	4.1	0.2	-0.3
Agriculture	2.0	0.1	-0.2
Law	3.4	0.1	-0.4
Humanities	1.0	0.04	-0.2
Non-Enrollment	20.4	-3.3	-3.3

Covariate Balance, conditional on enrolling in higher education

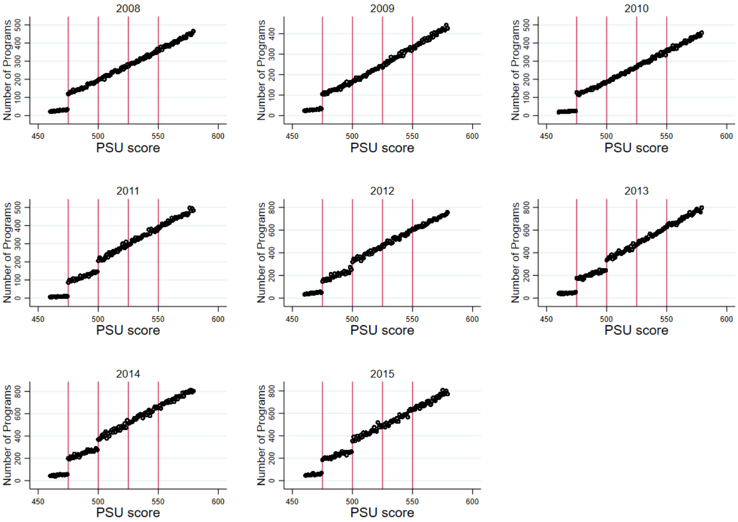
Table: Covariate Balance around Grant Eligibility Cut-off

	Baseline (β_0)	RD Estimate (β_1)	SE ($\hat{\beta}_1$)
High School GPA	5.731	0.006	0.009
# Working Family Members	1.158	-0.000	0.012
# Studying Family Members	0.102	-0.004	0.005
Female	0.529	-0.004	0.005
Single Mother HH	0.192	-0.005	0.005
Academic Parents	0.444	-0.017	0.011
Took Science Test	0.663	0.001	0.010
Municipal School	0.273	0.010	0.008
Subsidized School	0.672	-0.019*	0.010
Academic School	0.810	-0.014*	0.008

Back

Number of Programs as a function of PSU

Back



Difference in Marginal Effects

The marginal effect of characteristic x_{jk} on the choice of j at the cut-off is:

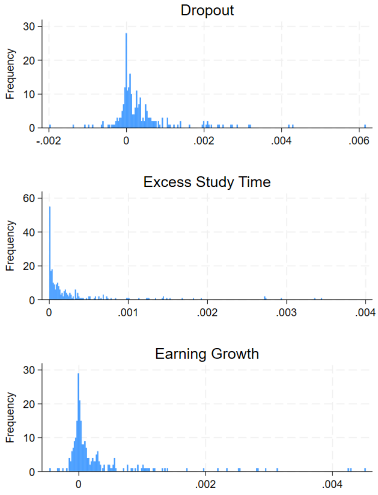
$$\frac{\partial Pr(j|g, PSU_i^* = 0)}{\partial x_{jk}} = \tau_k^g \times Pr(j|g, PSU_i^* = 0)(1 - Pr(j|g, PSU_i^* = 0))$$

There are $2 \times |J|^2 \times |K|$ marginal effects. Here we plot the difference in marginal effects for 3 characteristics, considering only the effect of x_{jk} on j.

Average ME of Dropout for Grant recipients: -0.16pp.

Average ME of Dropout for Loan-Takers: -0.2pp.

Back



Identification of Δ_k: Logit Case

Consider a case with two alternatives $j \in \{1,2\}$ where the structural model is:

$$U_{ij} = \tau^g x_j + \delta^g z_j + \varepsilon_{ij}.$$

Identification of Δ_k: Logit Case

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Instead, we estimate based on:

$$U_{ij} = \tilde{\tau}^g x_j + \varepsilon_{ij}.$$

Identification of Δ_k: Logit Case

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Instead, we estimate based on:

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In this case, the log-likelihood function is:

$$ln(L) = \sum_i \sum_j \mathbb{1}\{j(i) = j\} ln(\tilde{Pr}(j|g)),$$

$$\text{where} \quad \tilde{Pr}(j|g) = \frac{exp(\tilde{\tau}^g x_j)}{exp(\tilde{\tau}^g x_1 + \tilde{\tau}^g x_2)}.$$

Identification of Δ_k: Logit Case, continued

From the previously described problem, the maximum likelihood estimator of $\tilde{\tau}^g$ is:

$$\hat{\tilde{\tau}}^g = ln\left(\frac{x_2 - \bar{x}^g}{\bar{x}^g - x_1}\right)/(x_1 - x_2),$$

where $\bar{x}^g$ is the empirically observed mean of x among financial aid type g.

Identification of Δ_k: Logit Case, continued

From the previously described problem, the maximum likelihood estimator of $\tilde{\tau}^g$ is:

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where $\bar{x}^g$ is the empirically observed mean of x among financial aid type g.

- By the WLLN: $plim(\bar{x}^g) = Pr(1|g)x_1 + (1 - Pr(1|g))x_2$

Identification of Δ_k: Logit Case, continued

From the previously described problem, the maximum likelihood estimator of $\tilde{\tau}^g$ is:

$$\hat{\tilde{\tau}}^g = ln\left(\frac{x_2 - \bar{x}^g}{\bar{x}^g - x_1}\right)/(x_1 - x_2),$$

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- By the WLLN: $plim(\bar{x}^g) = Pr(1|g)x_1 + (1 - Pr(1|g))x_2$
- Using the continuous mapping theorem, this implies:

$$plim(\hat{\tilde{\tau}}^g) = ln\left(\frac{Pr(1|g)}{Pr(2|g)}\right)/(x_1 - x_2)$$

Identification of Δ_k: Logit Case, continued

From the previously described problem, the maximum likelihood estimator of $\tilde{\tau}^g$ is:

$$\hat{\tilde{\tau}}^g = ln\left(\frac{x_2 - \bar{x}^g}{\bar{x}^g - x_1}\right)/(x_1 - x_2),$$

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- By the WLLN: $plim(\bar{x}^g) = Pr(1|g)x_1 + (1 - Pr(1|g))x_2$
- Using the continuous mapping theorem, this implies:

$$plim(\hat{\tilde{\tau}}^g) = ln\left(\frac{Pr(1|g)}{Pr(2|g)}\right)/(x_1 - x_2)$$

Inserting the population probability based on the true model:

$$plim(\hat{\tilde{\tau}}^g) = \tau^g + \delta^g \frac{z_1 - z_2}{x_1 - x_2}$$

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Appendix to Chapter 3

Locus of Control Questionnaire

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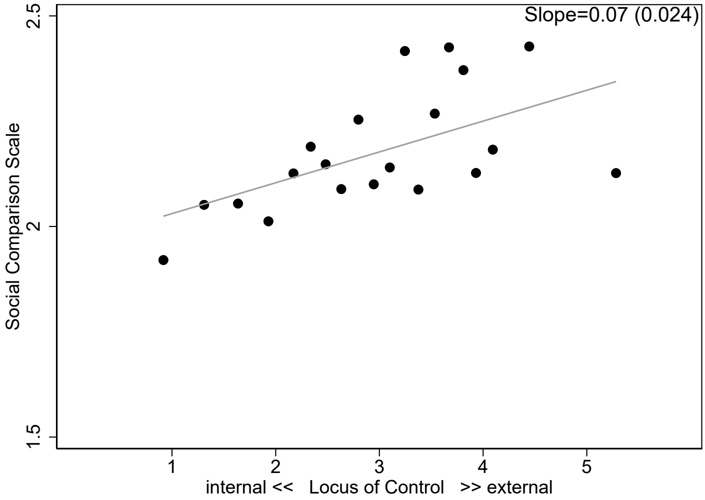
- **Locus of Control**: Likert-scale ranging from 1 (disagree completely) to 7 (agree completely); standard ten questions routinely used (Nolte et al., 1997), e.g.:
  - *I have little control over the things happening in my life.*
  - *You have to work hard to be successful.*
- Following previous studies (Cobb-Clark and Schurer, 2013; Specht, Egloff, and Schmuckle, 2013; Richter et al., 2013), we combine seven items into one equally weighted score; standardized using the sample mean and standard deviation:

$$LOC_i = \frac{\frac{1}{7}\sum_{j=1}^{7} Item_{j,i} - SMEAN(\frac{1}{7}\sum_{j=1}^{7} Item_{j,i})}{\sqrt{SVAR(\frac{1}{7}\sum_{j=1}^{7} Item_{j,i})}}$$

Correlation between LOC and External Comparisons



Treatment: Manipulation of Perceived Wealth Standing

Now I would like to talk with you about wealth. One can divide households in Germany into five categories of wealth. Wealth in this context refers to net wealth. That is, it is equivalent to the total household wealth, including, for instance, cash, savings accounts, stocks, or real estate, and subtracts debts, such as credit loans, mortgages, or credit card debt. Please indicate to which category your household belongs:

Control Group	**Treatment Group**
Up to 2,500	Up to 275,000
2,501 to 11,000	275,001 to 468,000
11,001 to 27,000	468,001 to 722,000
27,001 to 112,000	722,001 to 989,000
More than 112,000	More than 989,000

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Risk Measure: Elicitation & Estimation Framework

	Payoffs	EV	S.D.	CRRA-Interval
Lottery 1	(50, 50)	50	0	$[7.51, \infty)$
Lottery 2	(45, 95)	70	25	$[1.74, 7.51]$
Lottery 3	(40, 120)	80	40	$[0.812, 1.74]$
Lottery 4	(30, 150)	90	60	$[0.315, 0.812]$
Lottery 5	(10, 190)	100	90	$[0, 0.315]$
Lottery 6	(0, 200)	100	100	$(-\infty, 0]$

Estimation

- Random Preference Model: $CRRA_i^* = \tau \times Treatment_i + \mathbf{X_i}'\beta + \varepsilon_i$
- MLE with assumption: $\varepsilon_i \sim \mathcal{N}(0, \sigma_\varepsilon^2)$; Interval Regression
- Advantage: clear interpretation of τ

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Treatment Effect on Estimated CRRA Parameter

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	CRRA Paramter			
	(1)	(2)	(3)	(4)
Treated	-0.531*	-0.561**	-0.535*	-0.551**
	(0.282)	(0.279)	(0.281)	(0.277)
Treated × LOC			-0.953***	-0.952***
			(0.283)	(0.278)
LOC			0.566***	0.385***
			(0.208)	(0.213)
Observations	914	914	914	914
Covariates	No	Yes	No	Yes

Treatment Effect on Perceptions

Back

- As intended, the treatment induced participants to sort into lower categories Details
- The sorting aligns well with participants actual wealth levels
- The treatment shifts participants perceptions about the income/wealth distribution:

	(1) Income Top 10%	(2) Median Net Wealth	(3) Wealth Top 10%	(4) Rel. Wealth
Treated	0.293**	0.240	0.483**	-0.172***
	(0.139)	(0.148)	(0.231)	(0.062)
Sample	SOEP-IS	respondi	respondi	respondi
Observations	865	987	987	987

Sorting across Wealth Categories, by Treatment Group

Back

Control Group		Treatment Group	
Wealth Category (in)	% responses	*Wealth Category (in)*	% responses
<2,500	27.05	<275,000	79.01
2501 - 11,000	20.00	275,001 - 468,000	12.74
11,001 - 27,000	11.59	468,001 - 722,000	5.19
27,001 - 112,000	16.82	722,001 - 989,000	1.65
>112,000	24.55	>989,000	1.42

Framework linking Risk-Taking, LOC, and Relative Comparisons

Consider a decision-maker who values consumption both absolutely and relative to others:

$$U(c) = (1-\mu)v(c) + \mu g(F_s(c)),$$

where $F_s(c)$ is the decision-makers subjectively perceived cdf of consumption in the population.

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- At the same time, high μ individuals will respond more strongly to any perturbation of $F_s(c)$

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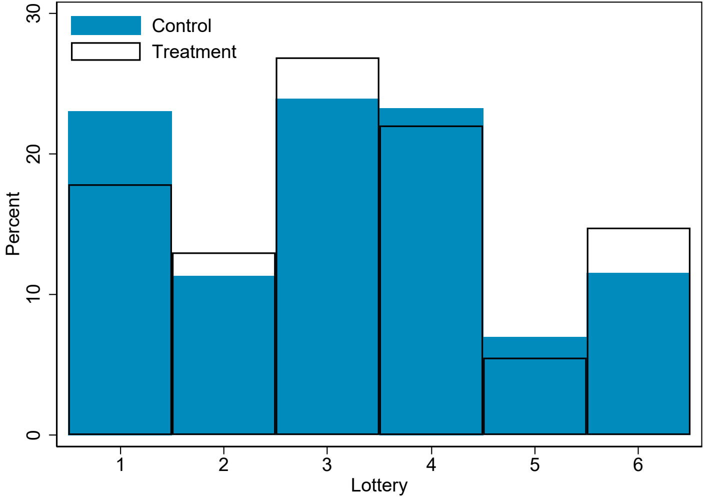
Distribution of Lottery Choices by Treatment Status



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